Integrating Automated and Humanistic Approaches: A Methodological Case Study of Teachers' Digital Professional Growth

Corrado Matta[1][a], Susanna Nordmark[2][b], Kristina Holmberg[1][c], John Rack[1][d], Mattias Davidsson[2][e] and Italo Masiello[2][f]

[1]*Department of Education, Linnaeus University, Universitetsplatsen 1, Växjö, Sweden*

[2]*Department of Computer Science and Media Technology, Linnaeus University, Universitetsplatsen 1, Växjö, Sweden*

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Abstract: This paper presents a methodological case study on teachers' digital professional development, emphasizing the integration of automated and humanistic approaches. Drawing from a four-year pilot project led by the research group, we explore how three distinct analytical methodologies—manual discourse analysis, text mining, and large language model-assisted thematic analysis—were employed to examine teachers' discursive practices regarding digital learning materials. The study investigates how integrating these methodologies enhances our understanding of digital learning material-related discourses and their evolution over time. Key findings reveal two primary conceptualizations: digital learning materials as pedagogical/effectivization tools and as complementary to analogue resources. The integrated approach demonstrated advantages in mitigating methodological biases, improving reliability, and enabling a richer analysis of diverse data sources. This work contributes to the development of robust analytical frameworks for studying the intersection of technology and pedagogy in educational settings.

1 INTRODUCTION

In this paper, we describe and discuss a case study of methodological integration applied to a study of teachers' digital professional development. The paper aims (a) to describe how three different analytical approaches – large language model (LLM), text mining, and traditional humanistic discourse analysis – were integrated to study the discursive dimension of teachers' digital professional development and (b) to discuss the methodological advantages of this integration.

The paper begins in Section 2 with a description of the background project of which the described experiment is a part. Section 3 describes the three different methodologies used in our case and their results. In section 4, we explain how the results from the three approaches were integrated and discuss the advantages of our integrative approach.

2 BACKGROUND

Guided by principles of Implementation Science, the research group at Linnaeus University has led a four-year pilot project to enhance teachers' digital competencies, foster data-driven learning, and utilize Visual Learning Analytics (Masiello et al., 2023; Nordmark et al., 2024). This collaboration included researchers, municipalities, schools, and leading providers of Digital Learning Materials (DLMs) in Sweden.

The project has involved extensive data collection, including interviews, observations,

[a] https://orcid.org/0000-0003-2282-8071
[b] https://orcid.org/0000-0001-7313-1720
[c] https://orcid.org/0000-0002-2924-4100
[d] https://orcid.org/0000-0001-7525-6180
[e] https://orcid.org/0000-0002-9474-6879
[f] https://orcid.org/0000-0002-3738-7945

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logbooks, and surveys. As the data analysis phase started, the team agreed on a set of sub-studies, each providing a part of the picture of teachers' digital professional development.

The first sub-study the team decided to work on is the object of this paper. This first sub-study investigates the participating teachers' discursive practices centered on DLMs and was motivated by the following research questions:

RQ1: What ideas about the concept and role of DLMs emerge from the perspectives of actors involved in a school digital transformation project? How do these ideas vary over time and across different participants?

RQ2: What expectations regarding DLMs are reflected in the data? How do these expectations differ over time and among various participants?

2.1 Methodology of the Sub-Study

The sub-study focused only on the teacher and school principal interview data. This data set consisted of transcripts from 22 semi-structured interviews with 44 teachers and three school principals. The interviews were organized into three rounds over three years, one round each year.

All interviews were transcribed, segmented (one segment for each turn-taking), and diarized. The data set was annotated specifying, for each segment: speaker, school, municipality, taught subjects, grade, date of the interview, interview round, and the DLM used.

After discussing which analytical approach to use, the team determined to employ three different approaches. Each approach and its results are described in the next section.

3 ANALYSES AND RESULTS

This section contains a discussion of the three analytical approaches used in three sub-studies of Teachers' DLM discourses. The three different lines of analysis are discussed in detail in the three separate studies (Holmberg et al., 2025; Masiello et al., 2025; Matta et al., 2025), while this article collects the aggregate summary analysis. Each of the following three subsections summarizes the methodology and results of one of these three studies.

The summaries in this section are brief and only describe the methodology and the most central results of the separate studies. We discuss the validity of each analytical approach in section 4.2 and refer the reader to the individual studies for a discussion of the reliability of the instruments.

3.1 First Approach: Manual Discourse Analysis

This section presents the discourse analysis of the interview data (Holmberg et al., 2025), guided by Laclau and Mouffe's (1985) framework and Gee's procedural approach (Gee, 2001), which emphasize agency and the creation of discursive patterns within social practices. We call this approach *humanistic* to emphasize the centrality of the researchers' interpretive competence as the main analysis tool (Pääkkönen & Ylikoski, 2021). Discourses are conceived as semiotic dimensions of social practices (in this case: the use of DLMs). Through participation in the project, teachers and principals develop linguistic repertoires that shape their representations of what DLMs are, their functions, and their ideal characteristics. These representations, termed *discursive formations*, are inferred through observable linguistic activities.

Two members of the research team worked on the analysis of the data, which involved three steps. First, the data were reduced by identifying all the segments related to DLM concepts and functions. Secondly, the reduced data were coded by grouping relevant segments thematically to reflect participants' conceptualizations, idealizations, and expectations of DLMs. Finally, discursive formations were identified by classifying themes into distinct discourses representing conceptualizations, idealizations of, and/or expectations about DLMs.

3.1.1 Results and Interpretation

The list of themes resulting from the coding process and their classification into discursive formations is found in the Appendix. The analysis resulted in three representations of the concept and idealized image of a DLM.

The first conceptualization conceives the DLM as a Pedagogical Tool and focuses on DLMs as instruments to enhance learning outcomes, emphasizing DLMs as capable of improving teacher-student interaction, generating multimodal representation of subject contents, supporting and scaffolding reasoning, and affecting learning goals. Hence, DLMs have an active impact on students' learning.

In contrast, the second conceptualization depicts the DLM as an Effectivization Tool. According to this idealization, DLMs are a means to streamline educational processes, enabling task optimization, monitoring, communication with students or parents, and integration while maintaining teacher control. This conceptualization differs from the first, as DLMs have a more infrastructural and peripheral role in the teacher's pedagogy. They do not impact learning directly but support the teacher in all the activities that are ultimately aimed at students' learning.

The final conceptualization focuses on *DLM and the Digital/Analog Divide.* This final conceptualization highlights tensions between digital and analog materials, with "hybrid" uses of DLMs conceptualized as a balance, especially towards the end of the project.

The findings show that the teachers' discursive practices changed over time. Participants gained deeper insights into the strengths and limitations of these tools, improving their ability to integrate them effectively. Moreover, changes in the teachers' conceptualizations might also be a result of a shift in the broader social discourse concerning the digitalization of the educational sector. This interpretation concerns the third discursive formation, which emerged towards the end of the project parallel to an ongoing shift in the public discussion about the use of digital tools in schools.

3.2 Second Approach: Text Mining

The second approach employed a text-mining analysis of the interview data (Matta et al., 2025), using statistical algorithms applied in Python (version 3.12.3) and R (version 2024.09.1+394).

A text corpus was built using the interview data sets, where each segment constituted a document. The annotated information was included in the corpus as document variables. The resulting corpus consisted of 2262 documents, 8 variables, and 34730 tokens (i.e., the number of words in the whole corpus), with a mean of 15.36 tokens per document and a standard deviation of 17.64 tokens.

Four analytical tools were used to analyze the corpus.

First, we performed sentiment analysis using the KBLab Sentiment Analysis classifier, a transformer-based neural network developed by KBLab at the Swedish Royal Library (Hägglöf, 2023). Trained on a dataset of 165,000 manually labeled Swedish texts. The classifier categorizes sentiment into positive, neutral, or negative with an estimated accuracy of 80%.

The second approach we employed was *Correspondence Analysis* (FactoMineR, Factoextra). This approach explores associations between sentiment – i.e., values of the categorical variable "sentiment" – and project rounds. Using dimension reduction (Singular Value Decomposition), it mapped the co-occurrence of categorical values in a two-dimensional space (Husson et al., 2024; Kassambara & Mundt, 2020).

The third analysis we applied was *Keyness Analysis* (Quanteda Textstats). Here, we identified words and phrases significantly differing across rounds. Terms from the final round were compared with earlier ones using Chi-squared statistics (Benoit et al., 2024).

Finally, we used *Topic Modeling* (SeededLDA), and, more specifically, Applied Latent Dirichlet Allocation (LDA) to uncover thematic clusters in the data, identifying topics as word groups with shared themes (Watanabe & Xuan-Hieu, 2024).

3.2.1 Results and Interpretation

Correspondence Analysis: Sentiment evolved from neutral in the early stages to negative mid-project and positive near the end. This reflected initial technical concerns, giving way to constructive views as participants adapted to DLMs.

Keyness Analysis: Early discussions focused on technical issues (“computer,” “platform”), while later rounds emphasized pedagogical aspects (“understand,” “exercise”) and the complementary role of DLMs alongside traditional materials (“complement,” “book”). Participants increasingly framed DLMs as supplementary resources rather than replacements.

Topic Modeling: Identified five relevant topics, forming two main thematic clusters: (1) DLMs as pedagogical/effectivization tools and (2) DLMs in relation to analog materials.

Keyness analysis and topic modeling revealed two primary representations of DLMs: DLMs as pedagogical/effectivization tools and as complementary to analog teaching materials. The first representation emphasizes the use of DLMs either as tools that impact learning directly or as tools that simplify teachers' work. The choice of merging these two conceptions into a single representation and not as two different ideas as in the case of manual discourse analysis was mainly based on topic modeling, which indicated that the pedagogical and effectivization features often occurred together.

The second representation, more clearly emerging as an independent thematic cluster, emphasized the tension between digital and analog pedagogical tools, where DLMs were discussed only in relation to this tension. We introduced here the concept of boundary object (Fleischmann, 2006; Fox, 2011) to describe the DLMs. According to this theory, the way of using language to conceptualize and idealize DLMs emphasizes the ongoing debate in the educational sector concerning the primacy of digital or analog pedagogical approaches and sees the DLM as an object that constitutes and maintains this tension.

Correspondence analysis indicated that sentiment shifted towards positive over time, which is consistent with the interpretation of the data in the manual discourse analysis, indicating that teachers developed a deeper understanding of educational technologies.

3.3 Third Approach: LLMs

The third analytical approach was to employ LLMs to support the thematic analysis of the interview data (Masiello et al., 2025).

The analysis was conducted using the ChatGPT-4o, guided by Braun and Clarke's (2013) thematic analysis framework. This third analysis focused on teachers' and school principals' systems of expectations about DLMs. The analysis started with an initial coding, where relevant data segments were identified based on recurring topics and phrases, and a custom stop-word list was applied during preprocessing. To assess thematic relevance, recurring terms (e.g., we have, has been, not really) were extracted. The second step involved developing themes from the initial codes. Codes were grouped into themes such as Teacher Confidence, DLM Integration, Student Engagement, Challenges, and Outcomes. Themes were refined iteratively for accuracy. The analysis concluded by focusing on temporal comparisons. Themes were analyzed across different stages (e.g., early vs. late project phases) to identify shifts in perspectives.

3.3.1 Results and Interpretation

The analysis highlighted key themes, categories, and codes:

Expectations and Idealized Views

- Interactive and Dynamic Learning: Anticipated enhanced student engagement through features like multimedia, interactivity, and gamified learning (fun, interactive, video, and games).
- Personalized Learning: Belief in digital tools' ability to tailor lessons to individual needs (adjust content, tailor lessons, review).
- Teaching Efficiency: Expected to simplify workloads with automated grading and resource organization (automate tasks, save time).

Challenges with Content and Implementation

- Content Quality and Alignment: Digital materials often lacked depth or curriculum alignment (not aligned, fit to lesson).
- Technical and Logistical Barriers: Teachers faced platform difficulties, glitches, and steep learning curves (troubleshooting, not simple).
- Student Engagement and Digital Literacy: Not all students adapted well to digital tools, with varying competence levels (not comfortable, not engaging).

Temporal Evolution of Perspectives

- Early Phase (2021): Optimism about digital tools' potential for innovation, engagement, and personalization (transform teaching, make it easier).
- Later Phase (2024): A pragmatic focus on high-quality content and effective integration, with less emphasis on transformative change (takes time, need to adapt).

This analysis revealed how expectations of DLMs evolved over time, providing valuable insights into their adoption and integration into educational practices.

4 METHODOLOGICAL DISCUSSION

This section describes the approach used to integrate and compare the three different lines of analysis and discusses the advantages and limitations of this approach.

4.1 Integrative Procedure

After having decided to approach our research questions from three different analytical perspectives, the team agreed on using an iterative and explorative procedure as a methodological approach for comparing and integrating the different insights.

The first stage of the procedure, after having determined the research questions, was to form three teams (each working with one of the analytical approaches), and each team would generate preliminary insights on their own. Next, a first comparison meeting was arranged in which each team presented their preliminary insights. Then, it was decided to interpret each insight not as a result that could be interpreted as an answer – albeit tentative – to our research questions, but rather as a new point of departure, an avenue for further analysis. This entailed ascribing limited credibility to the preliminary results and going forward with the three separate lines of analysis. Finally, a final meeting was arranged to compare the outcomes of the different analyses.

The results described in Section 3 represent the outcomes of this iterative and exploratory approach. The comparison of these outcomes revealed that the three lines of analysis converged on two discursive formations: the pedagogical/effectivization tool discourse and the analog/digital discourse. The next section discusses what level of credibility can be ascribed to the claim that these discourses indeed represent the structure of language use among the participants.

4.2 Advantages of Our Approach

The issue of the credibility of an interpretive theory, such as that which was generated by our iterative/explorative approach, is, in essence, a matter of distinguishing a plausible interpretation from an *interpretive artifact.* An interpretation is credible if it is likely to *represent* the actual social phenomena it targets. According to an inferentialist/pragmatist perspective (Suárez, 2004), which we assume, representation allows agents to make inferences about its target phenomenon. This means that an interpretation is credible if it can be used to make fruitful explanations and projections about the target. In contrast, an interpretive artifact is simply a result of forcing a narrative onto the data, which typically results in unreliable inferences.[7]

Assessing the credibility of an interpretation is best done by assessing the risks of interpretive artifacts and discussing the methodological ways to manage these risks. Three types of methodological risks affect our case, one for each of the lines of analysis.

Manual analysis relies on the interpretive schemes of the researcher and is, therefore, easily affected by *individual biases*. Humanistic interpretation rests on selecting what interpretations seem to best fit the data (Matta, 2022). Individual selection criteria can be biased towards explanatory schemes that are familiar or otherwise preferred, which introduces implicit weights or bias in the selection. As the process advances in the ladder of interpretation (coding → thematization → interpretation in terms of discursive formations), the risk of a researcher projecting such preconceptions on the data increases.

Text mining is based on statistical algorithms, which involve a risk of generating statistical artifacts. Researchers might be tempted to interpret statistical patterns as meaningful insofar as they are statistical patterns, but this increases the risk that some of the observed patterns in the data are simply statistical artifacts – that is patterns detected by the algorithm that depend systematic errors in the analysis or the data collection – and not existing relationships in the target phenomenon. For instance, the LDA algorithm used in our study can sometimes generate spurious topics by clustering terms that are lexically identical but used in different ways in different contexts.

Finally, using LLMs in research can be affected by different types of biases. Several sources (Ashwin et al., 2023; Schroeder et al., 2024) have discussed how using LLM for qualitative analysis might increase such risk. One source of bias can be the natural language data that is used to train the LLMs, which can be representative of other social groups than that which is analyzed. This will increase the probability that the chosen LLM produces interpretations that fit the context of the training data. Another source of bias can originate from the concepts and theories used to train the LLMs. It is important to highlight that LLMs do not generate analyses but report a statistical synthesis of the formulations used in training texts that the algorithm categorizes as *analyses*. Hence, whenever a LLM proposes a thematization, it is not proposing a model of the data but rather trying to summarize the textual

[7] For instance, someone could interpret a chair as a jacket. This interpretation will allow the interpreter to infer that wearing it will warm her/him. The interpretation is made less credible by the fact that it generates unreliable inferences.

behavior of interpretations included in the LLMs' training data. As a result, LLMs will more likely "interpret" the interview data according to more recurring interpretive frameworks, which introduces a conservative bias in the interpretation (bolder interpretations are systematically excluded).

Our approach has several rewards, some of which provide strategies that manage – although do not eliminate – all of these risks. First, it exploits the advantages of automatized and humanistic approaches by combining the depth of humanistic interpretation with the breadth of automatized procedures. Manual interpretations are more sophisticated but cannot manage large datasets, whereas automatized methods allow for the analysis of large datasets but are typically superficial. Our approach establishes a balance between these two dimensions.

Secondly, its explorative and iterative character contributes to the outcome's reliability. Ascribing a lower level of credibility to the preliminary insights decreases the risk of falling for compelling narratives.

Moreover, it harnesses the value of methodological pluralism as an analytical tool by working with three separate lines of analysis and comparing iteratively the insights of all the approaches; there is no single method of analysis that acquires a leading position. This avoids the typical bias toward quantitative analyses, which affects many mixed-methods studies. This bias is the result of a methodological assumption, according to which qualitative methods are appropriate for hypothesis generation and quantitative methods are best for theory testing. We challenge this view by focusing on how the target phenomenon was modeled using the different approaches and reflecting on the assumptions that these models inherit from each approach.

Our approach provides a management strategy for the bias risks mentioned above. The iterative and comparative approach decreases the risk for both individual, statistical, and LLM-based biases by letting each line of analysis work as a watchdog for all others. If the LLM generates an analysis that is biased toward a social group, the humanistic analysis is likely to pick up that bias in virtue of its sensitivity for context. In the same way, if the humanistic interpretation is biased by the researcher's interpretive scheme, there is a chance that both the LLM and the text mining analyses will fail to confirm that insight, as the latter are less prone to cherry-picking. Furthermore, if the text mining analysis is based on a statistical artifact, the humanistic interpretation will plausibly find that pattern far-fetched by identifying spurious topics. Finally, the inclusion of a humanistic component in the analysis allows for bolder interpretation, decreasing the risk of interpretive conservatism.

It is important to highlight that our integrative approach provides strategies that manage epistemic risks but cannot eliminate these risks. We cannot exclude the possibility that the individual researchers who apply the humanistic interpretive approach will not suffer the same kind of biases that could affect the LLMs and text mining approaches. A human researcher can suffer from a conservative bias or miss a spurious topic by failing to catch that the same word is used in different ways throughout a data set. However, by pluralizing the analysis of qualitative data, the risk of such biases is arguably lower than when working with any of the three approaches in our substudy.

5 CONCLUSIONS

The integration of manual, automated, and LLM-assisted methodologies in this study has highlighted the value of methodological pluralism in educational research. By combining humanistic insights with automated and AI-supported approaches, we were able to uncover teachers' perspectives on the evolving roles of DLMs in school. This iterative and exploratory approach not only mitigated biases inherent in individual methodologies but also helped in generating a comprehensive understanding of DLM discourses.

The findings emphasize the potential of DLMs as tools for both pedagogical enhancement and operational efficiency while also revealing ongoing tensions between digital and analog educational resources. Our study underscores the importance of an interdisciplinary lens in addressing complex educational challenges, offering a methodological approach for integrating diverse analytical perspectives. Future research could expand this framework to other educational contexts, further validating its applicability and effectiveness.

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REFERENCES

Ashwin, J., Chhabra, A., & Rao, V. (2023). *Using Large Language Models for Qualitative Analysis can Introduce Serious Bias* (arXiv:2309.17147). arXiv. https://doi.org/10.48550/arXiv.2309.17147

Benoit, K., Watanabe, K., Wang, H., Lua, J. W., Kuha, J., & Council (ERC-2011-StG 283794-QUANTESS), E. R. (2024). *quanteda.textstats: Textual Statistics for the Quantitative Analysis of Textual Data* (Version 0.97.2) [Computer software]. https://cran.r-project.org/web/packages/quanteda.textstats/index.html

Braun, V., & Clarke, V. (2013). *Successful qualitative research: A practical guide for beginners* (1. ed.). SAGE Publications.

Fleischmann, K. R. (2006). Boundary Objects with Agency: A Method for Studying the Design–Use Interface. *The Information Society*, *22*(2), 77–87. https://doi.org/10.1080/01972240600567188

Fox, N. J. (2011). Boundary Objects, Social Meanings and the Success of New Technologies. *Sociology*, *45*(1), 70–85. https://doi.org/10.1177/0038038510387196

Gee, J. P. (2001). *An introduction to discourse analysis [Elektronisk resurs] theory and method*. Routledge.

Hägglöf, H. (2023). *The KBLab Blog: A robust, multi-label sentiment classifier for Swedish*. https://kb-labb.github.io/posts/2023-06-16-a-robust-multi-label-sentiment-classifier-for-swedish/

Holmberg, K., Matta, C., Nordmark, S., Masiello, I., Rack, J., & Davidsson, M. (2025). From Balance to Informed Criticism – Discursive Transformations in a Development Project on Digital Learning Material in Primary School. *Proceedings of INTED Conference*.

Husson, F., Josse, J., Le, S., & Mazet, J. (2024). *FactoMineR: Multivariate Exploratory Data Analysis and Data Mining* (Version 2.11) [Computer software]. https://cran.r-project.org/web/packages/FactoMineR/index.html

Kassambara, A., & Mundt, F. (2020). *factoextra: Extract and Visualize the Results of Multivariate Data Analyses* (Version 1.0.7) [Computer software]. https://cran.r-project.org/web/packages/factoextra/index.html

Laclau, E., & Mouffe, C. (1985). *Hegemony & socialist strategy*. Verso.

Masiello, I., Fixsen, D. L., Nordmark, S., Mohseni, Z. (Artemis), Holmberg, K., Rack, J., Davidsson, M., Andersson-Gidlund, T., & Augustsson, H. (2023). Digital transformation in schools of two southern regions of Sweden through implementation-informed approach: A mixed-methods study protocol. *PLOS ONE*, *18*(12), e0296000. https://doi.org/10.1371/journal.pone.0296000

Masiello, I., Matta, C., Holmberg, K., Nordmark, S., Rack, J., & Mohseni, Z. (2025). An AI Chat-Bot Thematic Analysis of Teachers' Expectations of Digital Learning Materials in Primary Schools. *Proceedings of INTED Conference*.

Matta, C. (2022). Tolkningens metodologi och selektiv abduktion. *Pedagogisk forskning i Sverige*, *27*(4), 37–61. https://doi.org/10.15626/pfs27.04.03

Matta, C., Nordmark, S., Holmberg, K., Davidsson, M., Rack, J., & Masiello, I. (2025). The Discursive Mechanisms of Teachers' Digital Professional Development: A Quantitative Approach. *Proceedings of INTED Conference*.

Nordmark, S., Augustsson, H., Davidsson, M., Andersson-Gidlund, T., Holmberg, K., Mohseni, Z. (Artemis), Rack, J., & Masiello, I. (2024). Piloting Systematic Implementation of Educational Technology in Swedish K-12 Schools – Two-Years-In Report. *Global Implementation Research and Applications*, *4*(3), 309–323. https://doi.org/10.1007/s43477-024-00130-w

Pääkkönen, J., & Ylikoski, P. (2021). Humanistic interpretation and machine learning. *Synthese*, *199*(1), 1461–1497. https://doi.org/10.1007/s11229-020-02806-w

Schroeder, H., Quéré, M. A. L., Randazzo, C., Mimno, D., & Schoenebeck, S. (2024). *Large Language Models in Qualitative Research: Can We Do the Data Justice?* (arXiv:2410.07362). arXiv. https://doi.org/10.48550/arXiv.2410.07362

Suárez, M. (2004). An Inferential Conception of Scientific Representation. *Philosophy of Science*, *71*(5), 767–779. https://doi.org/10.1086/421415

Watanabe, K., & Xuan-Hieu, P. (2024). *seededlda: Seeded Sequential LDA for Topic Modeling* (Version 1.4.1) [Computer software]. https://cran.r-project.org/web/packages/seededlda/index.html

APPENDIX

Discourse	Themes
DLM as a Pedagogical Tool	Teacher-adapted, Language functions, Multimodality, Learning analytics, Fun/Lively/Interesting, Students' Digital Competence, Reasoning, Flexibility, Explanations, Goal Fulfillment, Repetition, Layout.
DLM as an Effectivization Tool	Efficiency, Assessment, Specific Applications, Integration, Monitoring, Family, Language functions, Repetition, Teacher-adapted, Updated.
DLM and the Digital/Analog Divide	The divide between digital and analog materials, hybrid solutions